Visualizing High-Dimensional Chemical Abundance Space in GALAH DR2

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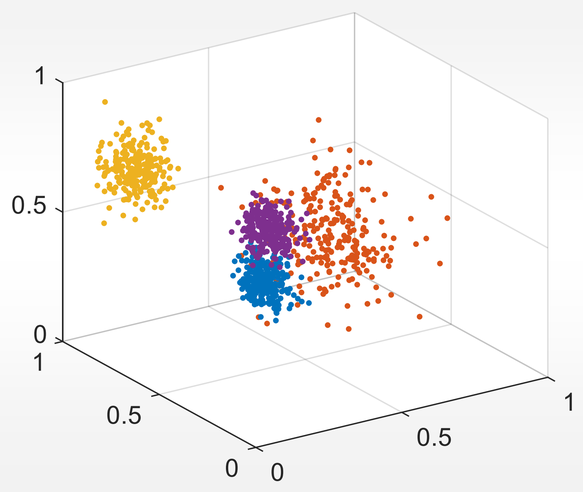
Aim: Visualize high-dimensional data to find interesting patterns and underlying structures

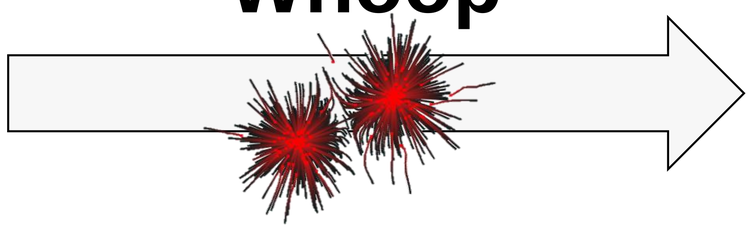
High-Dimensional Data



Gaussian random data with four clusters in 3D (also applicable to *n*D)

Filter high-dimensional data

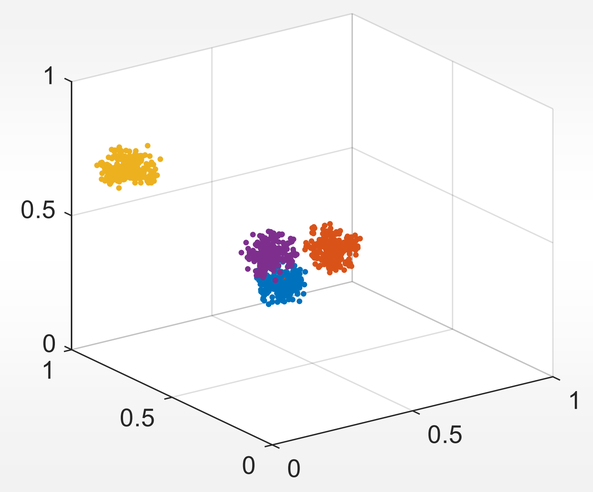
"Whoop"



Local Gradient Clustering (LGC)

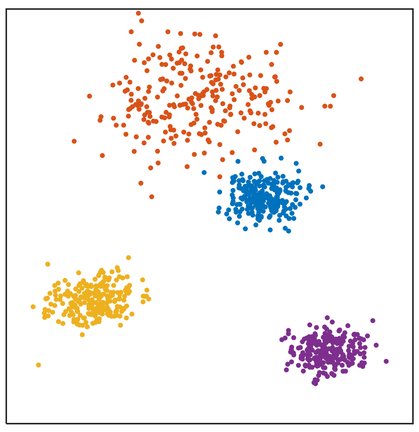
Shift points along the gradient of the kernel density estimator

Filtered Data



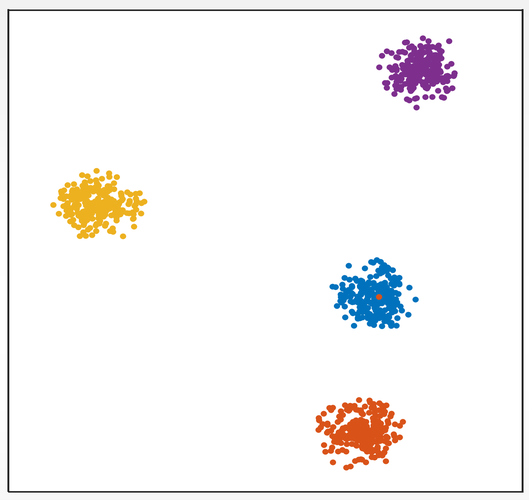
Clusters are separated in 3D

Dimensionality Reduction



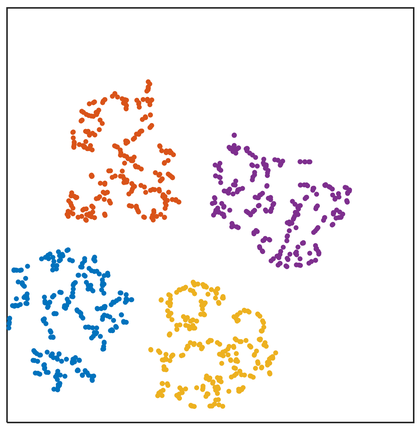
Landmark Multidimensional Scaling (LMDS [1]):
Clusters are **not well separated**.
Method is **fast**.

VS.



Proposed method (LGC+LMDS):
Clusters are **well separated** in the 2D projection.
Method is **fast**.

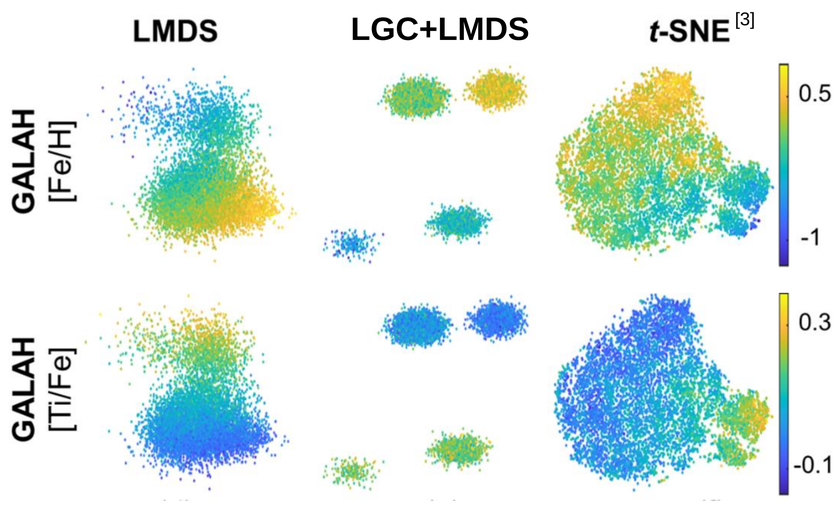
VS.



t-Stochastic Neighbor Embedding (t-SNE [2]):
Clusters are **well separated**.
Method is **slow**.

GALAH DR2

- **Dataset:** 10K observations are randomly chosen from the second data release of GALactic Archaeology with HERMES survey (GALAH DR2) [4] cross-matched with *Gaia* DR2 [5-6]. 10-D data set that consists of the following 10 stellar abundances are used: [Fe/H], [Mg/Fe], [Al/Fe], [Si/Fe], [Ca/Fe], [Ti/Fe], [Cu/Fe], [Zn/Fe], [Y/Fe], and [Ba/Fe]
- **Results:** LGC+LMDS shows cleaner separation of substructures in the 2D abundance-space than the original LMDS and t-SNE



References
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Summary

Key idea

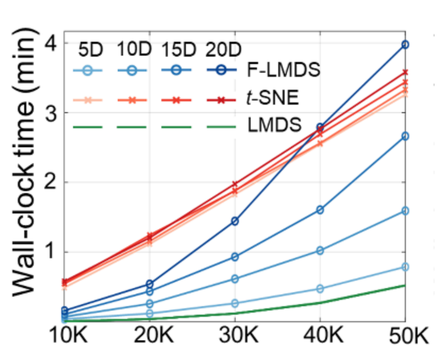
Filter the high-dimensional data so that potential clusters are well separated even after dimensionality reduction

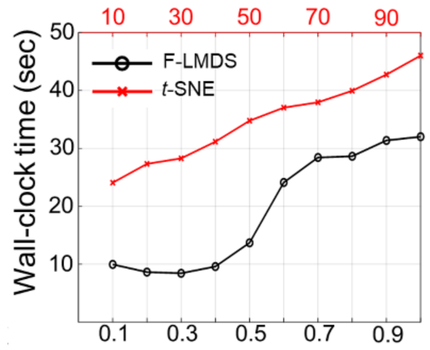
Method

I. Estimate density using Epanechnikov kernel [7-8]
II. Shift points upstream in kernel density gradient, resulting in cluster contraction [9]
III. Perform LMDS [1]

Advantages

- Clusters are **well separated** after the projection by preprocessing the data with local-based gradient clustering
- **Predictable** outcome with one parameter
- More **computationally scalable** than *t*-SNE, in terms of wall-clock time





Future Work

- A more sophisticated analysis of the different substructures gained from the LGC+LMDS results using GALAH DR2

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